

Operations Research in BASF's Supply Chain Operations

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June 10, 2014

Abstract In this article we highlight the application of Operations Research (OR) at BASF in the area of supply chain management (SCM) through the use of selected examples with annual cost savings ranging between several hundred thousand and several million €. We address special characteristics of the process industry that have to be dealt with and identify future research needs. The examples cover strategic, tactical, and operational topics encountered at BASF. We share our lessons learned based on our experience from past OR projects in SCM about challenges as well as benefits of standard and tailor-made OR solutions. In general, we find that the special characteristics often call for a modification or enhancement of standard OR models. Providing appropriate solutions therefore requires a joint effort of SCM, IT, and OR experts.

Keywords supply chain management · OR · mathematical programming · modeling · tailor-made solutions

1 Introduction

The last decades have seen a tremendous increase in the amount of data that companies collect and store. This is also true for BASF. The ability to exploit those data is considered to be an important driver of better

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decision making and improved profitability. McAfee and Brynjolfsson (2012) find that “companies in the top third of their industry in use of data-driven decision making were on average 5% more productive and 6% more profitable than their competitors” (p. 64). In order to realize such potentials, not only sufficient computing power is required, but more importantly the tailored application of mathematical methods and algorithms towards individual problems is critical. Conventional approaches and tools are mostly not sufficient. Instead, advanced mathematical competencies are needed to transform a real-world problem into a mathematical data-based problem, optimize relevant parameters, and provide quantitative results for decision support. In other words, there is a clear need for a stronger use of Operations Research (OR). Expertise in OR/mathematics at BASF is becoming a significant strategic opportunity in a world where complexity and the need for effectiveness as well as efficiency are increasing.

BASF has an in-house unit named *Scientific Computing* which is the competence center for mathematics. The unit consists of an interdisciplinary team with background in mathematics, statistics, chemistry, physics and quantitative economics. While there are certainly further units and individuals within certain business units of BASF applying OR methods, they are mainly focused on one particular method or application type. In contrast, the experts at *Scientific Computing* have an extensive methodological toolset at their disposal. It enables them to select the most appropriate solution approach for an individual problem and build dedicated models and specialized algorithms, if necessary.

Experience has shown that the latter is rather the rule than the exception to it. Due to the special characteristics in the process industry, in general, and BASF, in particular, readily available “standard” solutions can hardly ever be applied without any shortcomings or modification. For instance, one of BASF’s characteristics is its “Verbund” structure. “Verbund” refers to the efficient use of resources. Production plants at large sites are closely interlinked. The value chains (from basic chemicals to high-value-added products) are designed in such a way that the by-products of one plant can be used as the starting materials of another. Thus, the system saves resources and energy, minimizes emissions, cuts logistics costs and utilizes infrastructural synergies. For instance, the heat of production processes can be used as energy in other plants. The “Verbund” setup generates strong interdependencies between several businesses and cyclic relationships in the material flow, which represent challenges for standard mathematical models and approaches.

The main contributions of this paper are: (i) We illuminate the role OR plays at BASF, (ii) we provide examples of projects addressing decision problems in the area of strategic, tactical, and operational supply chain management (SCM) solved by OR techniques, (iii) we identify topics for future research in those areas, and (iv) we provide a detailed discussion on lessons learned and different views in the SCM and OR world.

The remainder of the paper is structured as follows. The next three sections address selected decision problems at BASF in the strategic (Section 2), tactical (Section 3), and operational (Section 4) domain as well as topics for future research. In Section 5 we summarize insights that we have gained from applying OR in the SCM area at BASF with regard to its value, but also with regard to the challenges encountered. Section 6 concludes the paper.

2 Strategic decision support

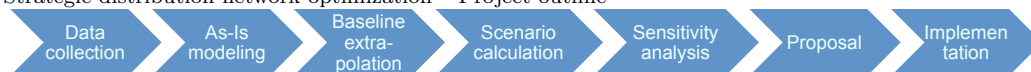
In the strategic decision domain we highlight three areas where the application of OR methods has generated value for BASF and still does. The first example is a very traditional OR problem: strategic distribution network optimization. Even though there are standard software packages available for addressing this problem, there is still room for enhancements. The second example is a special topic in the supply chain context, but a very important one for BASF and its “Verbund” structure. In this particular case we are concerned with the “Water Verbund”, *i.e.*, the supply and usage of fresh water and waste water. The third example deals with the logistics side and addresses the design of BASF's rail car fleet.

2.1 Strategic distribution network optimization

2.1.1 Description of the real-world example

Planning the future supply chain landscape is one of the key drivers for cost reduction in BASF. Amongst others, the aspects under consideration refer to the positioning of warehouses, the determination of appropriate plant capacities and the selection of the right modes of transportation given various supply, production, and distribution constraints. BASF operates in business units, each with their own supply chain planning units which optimize their sub-networks mainly on their own. This isolated approach most likely leads to a suboptimal setup from an overall BASF perspective. Moreover, new investments and company acquisitions constantly change the network design. Therefore, global network optimization projects have been successfully established as repetitive events to foster cooperation and make use of synergies in terms of transportation and warehousing costs as well as taxation aspects. Figure 1 shows how such a project is typically structured at BASF.

Fig. 1 Strategic distribution network optimization – Project outline

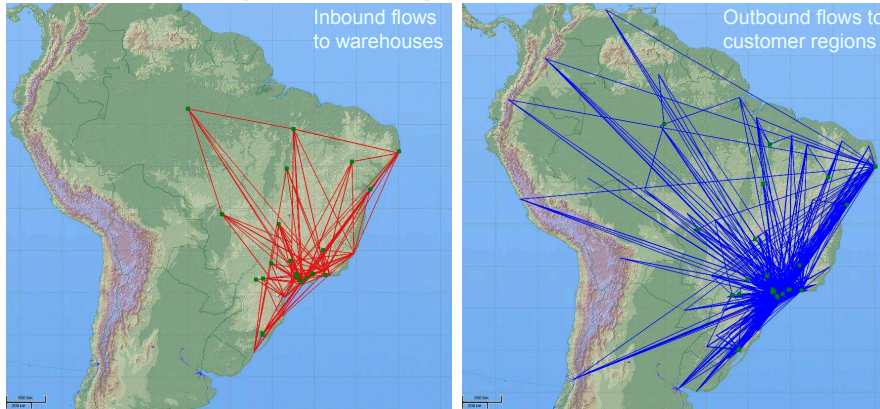


From a modeling point of view, such a project starts with a very time-consuming data collection phase in which historical data is extracted from the systems and needs to be prepared for optimization. By translating this data into the mathematical model world, we obtain the so-called “As-Is” model. After incorporating planned network changes and extrapolating demand and cost figures, we obtain the “Baseline” model which serves for cost comparison and project benefit analysis. Having strategic visions in mind, several predefined as well as project specific scenarios are optimized to get a glimpse of the overall optimization potential within the network. In these scenarios, typically, customer service level requirements are relaxed or improved, the absolute number of locations may be minimized or different distribution concepts (centralized, regional or local distribution centers) are tested to challenge the current situation and explore future opportunities. Finally, we arrive at a proposal, which can be seen as the most likely to be operated network design respecting all side constraints. Single measures are identified and quantified by the expected benefit.

Of major importance to the success of such a project is the communication of the modeling assumptions. Involving the business units early on in this process is key in order to get their trust in the final calculations. From the past projects we find that the cost saving potential amounts to 5-10% of logistics cost plus taxes, which corresponds to 5-20 million € per project.

A lot of standard software tools are available to carry out network optimization studies – still they need to be adapted to the needs of BASF’s complexity. Here, we are closely cooperating with Barloworld’s supply chain experts in enhancing their CAST tool. CAST is a powerful supply chain planning software application used for global supply chain network modeling, strategic network design and supply chain optimization, which also provides a graphical user interface to illustrate the computational results. Figure 2 presents a proposal obtained by the optimization model for parts of BASF’s distribution network in South America. The figure on the left shows the inbound flows from the ports to the warehouses (green dots). The figure on the right depicts the outbound flows from the warehouses to the customer regions.

Fig. 2 Strategic distribution network optimization – Sample network



Even though the standard mathematical model working in the background of the CAST tool contains many constraints that can be used to reflect the real-world setting, some relevant aspects for the BASF network in, e.g., South America are missing. In this region various kinds of inter-state taxes need to be paid with the possibility of balancing certain credits and burdens. Therefore, it is important to account for those tax aspects in an appropriate way. In the original CAST model this aspect could not be reflected appropriately, however. Upon our request, calculations for refundable and non-refundable taxes developed together with our OR experts have been incorporated into the tool. Even though aspects such as taxation might seem minor at first, they drive the ultimate result. In the future it is intended to make the tool even more flexible. Each user should be able to add his/her own (additional) constraints to the model without having to contact the CAST developers. Thus, necessary adjustments can be made more quickly by the company’s OR experts.

It is critical to the success of the project to obtain reliable data. Though all kinds of cost and volume movements from the past might be available, they are maintained differently from business unit to business unit and need manual adjustments. In terms of time, this easily adds up to half of the project timeline. However, it is essential to bring in the suggested changes into the implementation plan. Besides historical

data the forecasting accuracy as well as the modeling of transportation and warehousing costs play a crucial role. For transportation cost, we use regression analysis based on distances and drop sizes, if logistically reasonable, or we add original rates from the contracts, if these differ too much. Thus, the cost for proposed routes in the future can be estimated. In the financial reports warehousing costs are easily distinguished in fixed and variable costs. To correctly reflect the strategic nature of the project, parts of the fixed costs, such as labor, have to be translated into variable costs, however. It is crucial to check all of these rates with procurement early on in the process to get their final buy-in.

The challenge in solving our strategic network optimization problems within reasonable computation times comes from the huge size of the obtained networks. That is why efforts to keep the model at a reasonable size need to be made in the data preparation phase. In fact, there is a huge tradeoff between accuracy and applicability of OR methods.

2.1.2 Future research

Multi-objective optimization is a desirable direction for future development. Balancing cost with carbon footprint to increase sustainability, customer service lead times or the handling of complex distribution structures are only a few examples. Here, techniques for efficiently calculating the pareto-optimal frontier for further investigations of the solution space are in high demand.

Even more important and crucial for the success is finding a robust solution, *i.e.*, a solution that is stable against forecasting errors and against small changes in the cost assumptions. In particular, in strategic network optimization, simple scenario-based (best- or worst-case) approaches are not suited to obtain one solution being good enough in all scenarios. Hence, techniques from simulation, stochastic programming, or robust optimization - if any of them were applicable to such large-sized instances - are highly sought after.

2.2 Water Verbund optimization

2.2.1 Description of the real-world example

As an example of a non-standard design problem in SCM we refer to the Water Verbund optimization problem at the BASF site in Antwerp (Kallrath (1999)). The motivation for this project in the mid-nineties was a shortage of fresh water from the river Schelde. The general problem can be described as follows. Water-consuming processing units require water of certain qualities measured in terms of impurities. If appropriate, waste water might be used instead of fresh water. Thus, some units may use waste water from certain other units instead of fresh water if they are properly connected by pipelines. Treatment and processing units have limited capacities. The investment of new, local treatment plants is another option. Contamination limits for outlet into the Schelde river have to be observed as well.

The developed mathematical model includes a free network flow topology, pooling (nonlinear), selecting pipes, treatments, and capacities (discrete) of the pipelines. The degrees of freedom are to construct additional pipes in order to increase waste water re-use or to build additional local re-processing units to save

fresh water. The target of the mixed-integer non-linear programming (MINLP) problem is to minimize the overall cost.

Back in 1997, the problem could not be solved by formulating a single (“monolithic”) model; instead, several models (*polylithic approach*, cf. Kallrath (2011)) were developed that interact with each other to find a solution; the solution of one model is the starting point of another. The result of the polylithic model were good proposals for network design. Based on these suggestions, additional pipelines were built. The project costs of about 250 k€ were well balanced by annual savings of 300 k€. Therefore, the amortization period of this project was less than one year.

2.2.2 Future research

Today the solver technologies have improved and the particular model described above can also be solved as a monolithic one. In general, many projects at BASF require polylithic modeling and solution approaches as a bridging technology. Those problems can be used as interesting cases and starting points for further improving the solver technologies with the goal that, after a few years, those problems can be solved by monolithic model formulations. Decomposition approaches, a subclass of polylithic solution techniques, should also be kept in mind as a valuable solution technique. In many situations they allow us to prove global optimality for hard problems (cf. Rebennack et al. (2009)), e.g., for non-convex nonlinear problems (NLP and MINLP), which are still very challenging.

2.3 Rail car fleet design

2.3.1 Description of the real-world example

In the logistics area of SCM there are also interesting design questions to be answered, such as the optimal design of BASF’s rail car fleet; cf. Klosterhalfen et al. (2013). In particular, answers have to be found to the following three questions: (i) Structure - Which types of rail cars should be used? (ii) Size - What is an appropriate number of rail cars of a specific type? (iii) Ownership - Should BASF buy additional rail cars of certain types to increase its ownership (instead of leasing)?

In this project the two major challenges in finding a solution are the following: First, the mathematical model needs to account for substitution between different rail car types. The product to be transported has certain minimum requirements regarding the rail car characteristics. One such characteristic is, *e.g.*, the material of the rail car. Higher quality rail cars can be used as substitutes for lower ones. For instance, iron rail cars can be substituted by stainless steel cars. Second, stochastic demand and travel times of the rail cars have to be taken into account. Considering each of these two aspects in isolation in a mathematical model is rather simple. It is the combination that makes it challenging.

The solution approach developed together with the fleet management team combines two standard techniques used in OR: mixed integer linear programming (MILP) supporting substitution between the different rail car types and stochastic inventory control approaches to derive safety stocks in order to account for

the uncertainties in demand and travel times of the rail cars. Compared to the existing planning and execution approach of the rail car fleet management team, the model identifies a reduction potential for the number of different rail car types from 41 to 9 (see Figure 3). This enables a reduction in safety stock of approximately 120 rail cars and thus direct cost savings of 8%. Those two aspects are clearly interlinked and therefore cannot be analyzed in isolation. The reduction in the rail car types is only possible due to the usage of more flexible types, which are more expensive. The safety stock reduction that accompanies the fewer types outweighs those additional costs, however. Moreover, the smaller set of different types has additional indirect cost advantages. It enables a parking strategy of the rail cars on the storage tracks where each type is assigned to a separate track. Thus, a requested rail car of a specific type can be more easily accessed and provided. In total, a cost saving potential of several million € is identified.

Fig. 3 Rail car fleet design – Proposal obtained from the optimization



2.3.2 Future research

As stated above, we use a sequential approach for dealing with the substitution aspect (Step 1: MILP) and the uncertainties (Step 2: stochastic inventory model). Therefore, we cannot guarantee to exploit the full optimization potential, which a simultaneous solution approach could. In theory, it is possible to directly include the substitution option into the stochastic inventory model and solve those problems simultaneously as a uni-directional lateral transshipment problem (see, e.g., Axsäter (2003) and Olsson (2010)). At the time that we conducted this project no efficient solution algorithms were available to deal with our real-world problem size, resulting in a transshipment problem with more than 20 locations. The existing enumeration methods are too time consuming. Due to the time constraints in the project, we were not able to pursue the development of an appropriate solution method ourselves. Therefore, we opted for the sequential approach. For future research we view it worthwhile to develop such a method and compare both approaches.

3 Tactical decision support

In the tactical decision domain, inventory management and optimization represent major issues where OR methods are applied and expected to deliver value in SCM. This is also true for BASF. Therefore, our first example, which deals with the determination of safety stock for a production plant, can be viewed as “standard” at first glance. However, it exhibits certain characteristics special to the process industry, which

make it challenging. The second example, the “Supply chain early warning system”, is not something that directly comes to mind when thinking about OR in supply chains and as such is rather non-standard. This system enables the early detection of industry trends and quantifies its impact on BASF’s supply chains. Therefore, it provides critical information for many other OR models used in the supply chain area. In the third subsection we address collaborative planning as an important issue for BASF due to its Verbund structure.

3.1 Inventory management

3.1.1 Description of the real-world example

As for basically every company, the right-sizing of inventories is critical for BASF in order to minimize its working capital cost while providing the promised customer service. In many cases the application of simple standard approaches that do not take into account the special characteristics of the analyzed real-world setting at BASF is insufficient as it either leaves cost saving potentials untouched or might prescribe stock levels that are too small for guaranteeing the target customer service.

One such example is studied in Klosterhalfen et al. (2014). They analyze a high-pressure reactor that produces a liquid chemical around the clock. Basically, the process is only interrupted for maintenance purposes. The chemical reaction within the reactor can be run at different rates, *i.e.*, it can be done at a lower or higher pace. The quality of the output is not affected as long as the run rate stays within a certain range. Consequently, the minimum and maximum run rates define the minimum and maximum production quantities that can enter the inventory each month. The run-rate adjustment represents the only feasible reaction to the stochastic customer demand. Due to technical reasons such a run-rate adjustment is only possible at regular intervals; in this particular case at the beginning of each month.

Standard inventory models usually do not consider such constraints on the production or replenishment quantities or at most they consider one of those constraints; oftentimes it is a capacity constraint on the production process which results in a maximum production quantity restriction. A tailored inventory model that takes those special characteristics into account can deliver considerable value. Compared to the simple standard inventory model without the quantity restrictions, which is currently used as an approximation, Klosterhalfen et al. (2014) identify a safety stock quantity saving potential of 12.3% for this particular company setting.

3.1.2 Future research

The above-described example highlights only one of BASF’s special requirements in the area of inventory management. Other prominent challenges refer to the better integration of production aspects into stochastic inventory models and the inventory management of products with an uncertain beginning of the selling season. The latter aspect is typical, *e.g.*, for the agricultural products business at BASF. Due to varying weather conditions the selling period of certain products starts earlier or later in a year and even the length of the selling season might vary. What complicates matters is that some of the final product components,

such as active ingredients, have a very long lead time and thus must be produced well in advance of the selling season. Moreover, capacity restrictions on formulation stages aggravate the planning challenge even further.

With regard to the first aspect, many of the existing inventory models dealing with stochastic demand are built for the distribution part of a supply chain. Their application to the production part usually requires various simplifications and assumptions that eventually drive the result. One such aspect is production time. We understand the production time as the time it takes from the creation of a production order until its receipt in inventory. That means, it represents the uncertainty time span during which demand variability needs to be buffered. The production time is the equivalent to the transportation lead time in the distribution part of the supply chain. The transportation lead time can be specified quite easily for each stock keeping unit (SKU), since it is (most of the time) independent from the transported quantity and from other SKUs. The production time, on the other hand, may be influenced by the produced quantity (and thus be endogenous) and/or depend on other SKUs in case of multi-product/-purpose production assets processing more than one SKU. If the production asset is blocked due to the production of one SKU, all following SKUs have to wait until their production can start which extends their production times. Therefore, specifying the production time for an SKU without taking into account the concrete production schedule is inevitably an approximation. This is required by those standard inventory models, however.

A similar separation between the optimization of safety stocks and the determination of an optimal production plan can be found in *Advanced Planning Systems* (APS) like SAP APO. Here, the safety stock is an input for the optimization of the production plan, even though the actual production plan determines the production time of the different SKUs, which in turn affects the required safety stock quantity. Therefore, an interesting area for future research in this field lies in the integration of production and inventory planning under uncertainty. Some models have been developed in this area, see, *e.g.*, Tempelmeier and Herpers (2010), Tempelmeier (2011), or Helber et al. (2013). But there are still limitations to overcome in order to make them applicable in practice. Moreover, the extension to multi-level/-stage settings, which are frequently encountered at BASF, is worthwhile exploring. Existing multi-echelon inventory models and available software tools based on the seminal works by Simpson (1958) and Clark and Scarf (1960) also face the above-mentioned challenges and lack a detailed reflection of the production part.

3.2 Supply chain early warning system – A predictive analytics approach for demand forecasting in the process industry

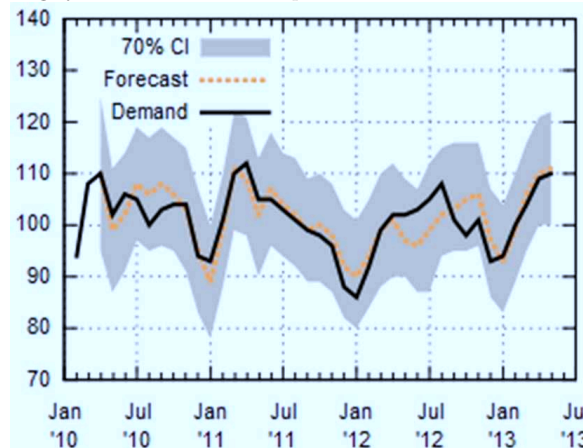
The current economic environment is characterized by volatility, uncertainty, complexity, and ambiguity (VUCA). The term VUCA originates from the military context (Stiehm and Townsend (2002)), but was later adopted by the business domain as well (Wolf (2007)). In particular, market volatility and supply chain complexity pose big challenges to top managers (Cecere (2013)). This is also true for BASF. Having a good idea about how industries and markets will develop and what their impact is on a supply chain, is crucial for initiating appropriate reactions to those developments and gaining a competitive advantage. By analyzing *historical* supply chain performance data a lot can be learned about influencing factors and

resulting responses within a supply chain. However, in isolation this information is of little use for the better steering of a supply chain. To do so it needs to be combined with *forward-looking* data about industries and markets.

This is the goal of the “Supply Chain Early Warning System (SC-EWS)” that has been developed over the last few years within BASF. It combines external industry and economic information (external indicators), BASF’s large internal information base (internal indicators), and new analytical approaches and methods. Thus industry and market trends are detected and related to the impacted businesses and supply chains within BASF. The time horizon on which the system (currently) focusses is 3-12 months.

For many businesses the model delivers a forecast accuracy above 90%. Figure 4 provides an example of a business unit forecast. The black line represents the actual sales quantities. The orange line is the generated point forecast. The grey area indicates the 70% confidence interval. It can be easily observed that the model predicts the up- and downswings very well. Moreover, the SC-EWS provides the businesses with a list of external/internal indicators that the model chooses to improve the forecast accuracy. For more details about the SC-EWS and topics for future research in this area we refer to Blackburn et al. (2014).

Fig. 4 Supply chain early warning system – Forecast example



3.3 Collaborative planning

Collaborative planning in two respects becomes increasingly important for BASF: (i) between different business functions within the same business unit and (ii) between different business units. With regard to aspect (i), the dominating business functions in the past have been “Production” and “Marketing”. Both functions are interested in producing as much as possible of a certain product, but for different reasons. Marketing wants to ensure that customer requests are always satisfied. Production wants to ensure a high utilization of their production assets. Little emphasis is put on the capital tied-up in inventory resulting from such a strategy. With the introduction of the “Supply Chain” business function and the transition from this rather volume-driven to a more value-based approach in recent years more coordination efforts are required between the different business functions at BASF. This is also known as Sales & Operations

Planning. OR methods can be extremely useful in this context by providing quantitative decision support. In case of raw material or product shortages, suggestions based not only on *volume*, but on *value* can be generated. Those suggestions can also take into account additional restrictions in the supply chain.

Aspect (ii), the collaboration between different business units, is particularly important for BASF due to its highly integrated Verbund structures. They create many interdependencies between different business units as they share parts of one and the same value chain. When it comes to the optimization of such chains, *e.g.*, in case of raw material shortages, ideally all the relevant data including price information are collected and plugged into an appropriate OR model that produces the optimal (most profitable) result. However, due to various reasons, business units do not directly share profitability information with each other. This hampers the above-described approach. Therefore, it seems interesting for future research to look for approaches that do not require this explicit information sharing, but still deliver (close to) optimal results.

4 Operational decision support

In the domain of operational decision support we distinguish between *scheduling* and *dispatching*. This is sometimes also reflected as the difference between *offline* and *online scheduling*, see Sgall (1998). Offline scheduling ideally assumes that all data of a problem are given, *i.e.*, we have full knowledge of the future. Of course, this is an approximation since our knowledge of the future demand or orders is uncertain. Offline scheduling is close to tactical production planning except for the length of the time horizon, the resolution of time, and, most importantly, all the many very detailed pieces of information which are oftentimes not recorded in company databases. Examples include the connection of plants or the number and characteristics of buffer tanks. Such data are even subject to rapid changes because plant setups are modified. Human planners have a large reservoir of creative exceptions when it comes to reactions to daily situations on the production floor, *e.g.*, they use rail cars as buffer tanks, exceed the capacity for a short time, persuade customers to take the ordered material somewhat earlier or later, or negotiate with customers to take a larger or smaller quantity of the material.

Online scheduling, or dispatching, as a special case of (combinatorial) online optimization (*cf.* Borodin and El-Yaniv (1998)), makes decisions based on past events and current data without any information about future events that are relevant for the current decision problem. Many decisions have to be made before all data are available and decisions once made cannot be changed. Online scheduling may involve current process control data, updated demand data and orders, but misses orders which may enter the system in the near future. However, those orders fall within the planning horizon for which the current schedule is to be determined. The goal is to exploit uncertain (with regard to the future) and incomplete information in such a way to improve the schedules' overall performance, *i.e.*, the quality of schedules over rolling time horizons. In contrast to stochastic optimization, where known data are subject to stochastic uncertainties, the uncertainty in online scheduling only arises from the uncertainty of future data.

For BASF's offline or online scheduling problems the following structural elements are typical:

1. multi-purpose (multi-product, multi-mode) reactors,
2. sequence-dependent setup times and cleaning cost,

3. combined divergent, convergent and cyclic material flows,
4. non-preemptive processes (no interruption), buffer times,
5. multi-stage, continuous, campaign & batch production using shared intermediates,
6. multi-component flow and nonlinear blending,
7. finite intermediate storage, dedicated and variable tanks.

Structurally, these features often lead to allocation and sequencing problems (*cf.* Kallrath and Wilson (1997)), knapsack structures (*cf.* Martello and Toth (1990)), or even to the pooling problem (*cf.* Fieldhouse (1993)). In strategic or tactical planning problems we prefer time-indexed models using a relatively coarse discretization of time, *e.g.*, a year, quarters, months or weeks are usually accurate enough.

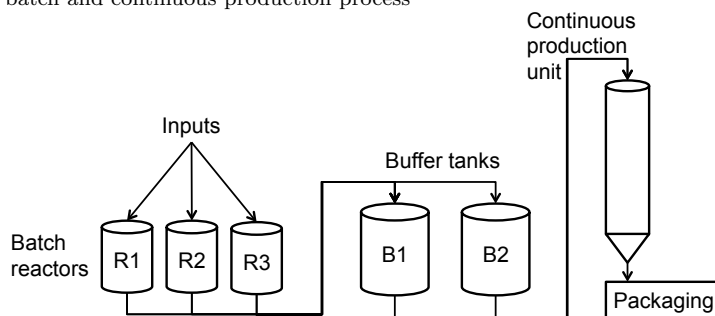
In scheduling problems, the focus on time is more detailed, and continuous time formulations (*cf.* Janak et al. (2006a)) are often preferable. Furthermore, we face (conflicting) goals that need to be aligned rather than a simple objective such as profit maximization: the optimal use of resources, minimal makespan, minimal operating cost or maximum profit versus more qualitative goals such as reliability (meet demand in time, proper quality, etc.) and robustness; such qualitative goals are often hard to quantify. It is common that the possibility to interact and to re-schedule, as well as the stability of solutions in case of re-scheduling are highly appreciated. Due to their complexity and special characteristics, scheduling problems often call for dedicated model formulations and specialized solution algorithms.

In this operational decision section we only describe one decision problem in detail: A scheduling problem which contains most of the features mentioned above. Afterwards, we outline a couple of challenges specific to the process industry that call for future research.

4.1 Combination of batch and continuous production processes

In Janak et al. (2006a) a large-scale scheduling problem faced in a very complex BASF plant is described and solved by using a continuous-time formulation, in which time is allocated to event points. The problem involves all of the structural elements from the above-stated list except for the sixth one (“multi-component flow and nonlinear blending”). Here we describe only a small part of the plant and only the major aspects and challenges. Raw materials are fed into up to three batch reactors and undergo a batch operation each time using the full batch size to produce an intermediate which is sent to two buffer tanks before being processed in a continuous unit (see Figure 5). Since certain products run faster on the continuous unit compared to their batch processing time on the reactors, the reactors can/must start prior to the start of the continuous unit to prepare the campaign and prefill the tanks. The challenge is to synchronize the batch and continuous production by exploiting the two buffer tanks to best meet the demand quantities and due dates of the individual products.

The time horizon for this scheduling problem is 4 to 8 weeks. In this time frame, about 10 to 20 different products need to be produced. These products fall into two categories. Products of type 1 are subject to tracing production batches for legal purposes. This implies to keep track of each batch produced on one of the reactors, to keep the tanks separate, and to empty each tank completely before recharging it with a new

Fig. 5 Combination of batch and continuous production process

batch. Products of type 2 are not subject to tracing, which technically implies that we can combine the two buffer tanks to one large buffer reservoir.

Apart from constraints such as the one above, multiple optimization criteria have to be taken into account. Of highest priority is that, ideally, the continuous unit should not be interrupted. Moreover, the second reactor should be used at a minimal number of batches because it should rather serve other products in the larger network topology. As the demand of the products does not exactly fit to what the three batch reactors with their individual batch sizes can produce in any combination, we also try to minimize both underproduction and overproduction. Minimizing the gaps between the batches on the individual reactors is another goal to be pursued if possible.

In order to solve this complex multi-criteria optimization problem, we apply a two phase approach: In Phase 1 we make the simplifying assumption that reactors are *always* available and can produce ahead to prefill the buffer tanks. Under this assumption we minimize the total interruption time of the campaigns on the continuous unit. Furthermore, we derive various lower bounds on certain quantities (indicated by the arrow below) by applying the following hierarchy of objectives in a lexicographic goal programming approach (see, e.g., Schniederjans (1995)):

1. minimize overproduction (demand vs. reactor batch sizes) → lower bound on unavoidable overproduction
2. minimize underproduction → lower bound on unavoidable underproduction
3. minimize interruption on the continuous unit → lower bound on unavoidable interruptions
4. minimize time for prefilling the tanks → ensures closest connection of the current campaigns and the associated reactor batches to the previous campaign
5. minimize the number of charges on reactor 2 → lower bound on the minimal number of batches on reactor 2.

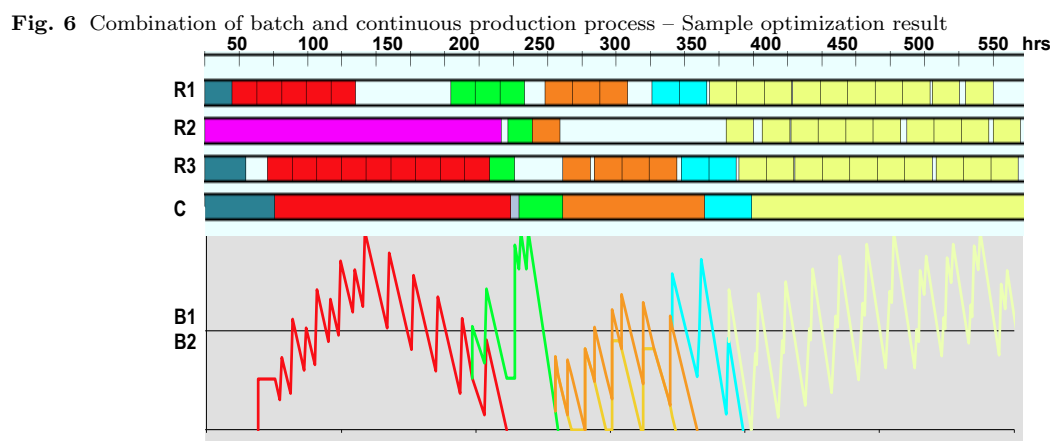
The Phase 1 results either provide useful information for the planner, such as the unavoidable over- and underproduction under ideal conditions, or they are used in Phase 2 to improve the numerical behavior of the problem and facilitate the determination of the optimal solution.

In Phase 2 we account for possible reactor blockades or the unavailability of the reactors. Such blockades might require a later start of a campaign on the continuous unit in order to avoid interruptions. Ideally, we like to deviate as little as possible from the campaign start determined in Phase 1. Therefore, we minimize the time shift by taking into account the lower bound on the unavoidable interruptions from Phase 1. Since

we are also interested in dense production schedules on the batch reactors we minimize the finishing time of the reactor finishing last, which ensures exactly this. Finally, we also minimize the number of batches on reactor 2 and overproduction under these new conditions. Overall, the hierarchy of objectives in Phase 2 can be summarized as:

1. minimize time shifts of the campaigns
2. minimize finishing time of the reactor finishing last
3. minimize number of batches on reactor 2
4. minimize overproduction.

The above-described approach produces a feasible schedule within 10 minutes which is optimal with respect to the outlined hierarchy of individual objective functions. Figure 6 shows a typical Gantt chart with the three batch reactors, the continuous plant and the two tanks aggregated to one large tank. The grey shaded area on the continuous plant C represents cleaning time. The grey-green shaded area on the reactors starting at time 0 indicate timespans at which the reactors are not yet available. The purple color represents a blockade. The red product campaign is characterized by batches following each other without gaps, while the yellow product batches show gaps. The tank diagram at the bottom nicely illustrates that tanks are prepared prior to the start of the continuous plant.



The model, implemented in GAMS, is embedded into SAP APO and has been successfully in use since 2006. The reasons for its success include a strong management support as well as a talented planner having a good understanding of all the details on the production floor.

The planner appreciates the tool a lot because it brings strong reliability into his daily work and helps to reduce his time spent on generating feasible schedules. Since the generated schedules reflect reality to a very high degree, the planner can rely on the fact that the tanks do not overflow or the continuous process does not have to be interrupted because a tank becomes empty. The explicit determination of unavoidable over- or underproduction represents another benefit. It provides valuable information for joint meetings of the production planner, the supply chain and marketing groups about the feasibility of the original (high-level)

plans created by those groups. Last but not least, the financial benefit of about 1-2 million € per year due to smoother operations and a better utilization of the production assets is highly appreciated.

4.2 Future research

Particularly in the area of detailed scheduling, we experience many special aspects of the process industry – a rich world requiring many detailed features to be considered. Modeling scheduling problems is a challenge in itself. In the first place, it would be an important research task to *develop a modeling language that is appropriate to describe scheduling problems*. Similar to algebraic modeling languages, which use the key objects *variables*, *constraints* and *objective functions*, and are thus ideal to implement mathematical optimization problems, the development of a scheduling language would be required that maps the key objects *units*, *resources*, *states*, *tasks*, *network topology*, *logical relations*, etc. and *goal criteria* to an appropriate mathematical structure, *e.g.*, mathematical optimization or constraint programming representations.

Structurally, scheduling problems are often multi-criteria optimization, where most of the objectives are hard to quantify, or feasibility problems rather than profit maximization problems. Plants are usually designed for producing a particular product portfolio, for which they are equipped with sufficient extra buffer capacity. As long as they smoothly produce this portfolio the potential for financial improvements appears limited. The only advantage in that scenario is that a mathematical optimization approach generates a reliable and feasible schedule independent of the individual who triggers the optimization. That means, production plans of similar quality are produced independent of a specific planner. Once the product portfolio is altered or even the plant setup itself is modified, the situation changes completely. For instance, the capacity of a plant might no longer be sufficient. Therefore, one runs into infeasibilities when trying to create a schedule. The solution approaches found in the literature are:

- *exact and deterministic methods* such as mathematical optimization including MILP and MINLP, graph theory (GT, *cf.* Krumke and Noltemeier (2009)) or constraint programming (CP, *cf.* Apt (2009)), or *hybrid approaches* in which MILP and CP are integrated,
- *meta-heuristics* (evolutionary strategies, tabu search, simulated annealing,) as described, for instance, in Michalewicz and Fogel (2000), or
- a *combination* of the former two types; that falls into the class of polyhedral modeling and solution approaches.

Exact and deterministic methods, or polyhedral approaches are preferable, because only they allow us to derive and prove unavoidable violations of constraints. Knowing that something is not possible can be of great help. Therefore, the challenge is still to *derive exact methods for real- world large-scale scheduling problems*.

5 Lessons learned

5.1 Benefits of OR in SCM

As the above-mentioned examples illustrate, OR can deliver great value in the area of SCM not only at BASF, but also in general. Besides the obvious monetary benefits, this primarily includes:

- A better understanding of real-world problems is generated.
- Transparency is created between various stakeholders who affect and are affected by the problem under consideration.
- Stronger confidence in decisions is created by basing them on a quantitative model analysis and by involving all stakeholders in the model-building process.
- A competitive advantage can be gained.

Due to the complex nature of the decision problems in the process industry, caused by the various special characteristics outlined above, simple solutions using either standard Excel functionality or standard APS models only are often insufficient. Most of the time, more advanced OR methods are required.

5.2 Challenges

In order to be able to unleash the potential of OR in SCM certain prerequisites have to be fulfilled and sometimes obstacles need to be overcome.

5.2.1 Different views

In larger companies SCM often follows strict hierarchical and organizational structures and thinks in terms of processes. OR, at least in its mathematical programming branch, *per se* focusses on the decision problem to be solved in the first place and does not care about such “artificial” constructs. Depending on the problem, it might affect several parts and responsibilities of the SCM organization. This also refers to the ownership of the required data that enter the OR model.

Concerning data one also encounters further difficulties. Data quality is one of them. There is often no common understanding across the various business units about the information to enter in specific data fields. Many times data fields are misused either intentionally or unintentionally. It is an important task of the SCM organization to create a common understanding. One facilitator in this respect can be the exposition of the clear value of an improved data quality, *e.g.*, by pointing out the value of OR solutions that inevitably rely on such data.

Data structures represent another difficulty. The way in which data are collected, aggregated, and stored is often not ideal or insufficient for usage in an appropriate mathematical decision problem. For instance, in the area of supply network planning, the demand in a period gets allocated directly to specific production sites/plants according to a predefined allocation fraction without considering the actual capacity and cost situation at the individual plants. Only these allocated demand quantities are stored in the system and

thus available for optimization later on. However, this allocation step itself represents an optimization problem. Another example refers to the desired customer quantity and due date. Oftentimes, not the actually requested quantity and date is entered into the system, but an adjusted quantity and/or a modified date. These tweaked numbers better fit the current product availability and are still acceptable for the customer (after some negotiations). For planning purposes the original numbers would be highly valuable, however. Therefore, it is wise to include an OR expert in the definition phase of processes and data structures, even if the direct need might not be apparent to everyone at an early stage. Modifying inappropriate structures from an OR perspective in retrospect is much more costly or even impossible. The advances in IT can also help alleviate the data challenges. Storage space nowadays comes at a very low cost. Coupled with the switch of a company's IT databases to in-memory technologies, which represents an opportunity for making necessary adjustments to the data structures from an OR point of view as well, the granularity problem or excessive access times for getting the right data out of the system might diminish in the future.

5.2.2 Standard and tailor-made solutions

In the area of SCM there are a lot of complex tasks to conduct, especially within large companies. In order to help manage this complexity and avoid a proliferation of individual solutions SCM organizations tend to define and strive for standards. While this might contain costs on the IT side in terms of lower maintenance, such a strategy also bears the risk of generating additional (and unnecessary) costs elsewhere in the businesses. For instance, if the standard approach does not model the real-world problem at an appropriate level of detail and consider all relevant aspects, it produces solutions with too large safety buffers or solutions which violate various constraints such as service level, capacity bounds which makes it inferior even to manual or intuitive planning results. For sure, this is a difficult trade-off to solve. While IT considerations should definitely play an important role in this, they should not be the dominating or sole decisive factor. After all, IT should act as a supporting function for the businesses, not as a limiting one. That is why at BASF the "Information Services & Supply Chain Operations" division strives towards *tailoring* their innovative, differentiated solutions to meet the business needs.

A standard or basic solution is definitely a good starting point. However, it should not be defined too narrowly or be inflexible. Having a standard (ERP) system/platform for storing and exchanging data between different interconnected businesses within the company is indispensable and a good basis for OR solutions (keeping in mind the above-mentioned obstacles that might have to be overcome with regard to data). In order to exploit the potential of OR to its fullest, especially in the area of planning support, this standard system, be it an ERP system or an APS, should allow for sufficient flexibility to plug in tailor-made solutions, if the readily available functionalities are not appropriate.

The detailed scheduling problem in Section 4.1 represents a good example for an application at the operational decision support level that calls for such a tailor-made solution. Instead of resorting to penalty techniques to reduce underproduction and delays, the solution explicitly computes and reports unavoidable underproduction and delays using the goal programming techniques. The reason and advantage of this ap-

proach over standard ones is that penalty terms in the standard model may lead to numerical problems and deliver solutions that are inferior and incomprehensible; *cf.* Kallrath and Maindl (2006), pp. 344.

The “water Verbund optimization” and “rail car fleet design” problems are highly beneficial tailor-made counterparts to the detailed scheduling problem in the strategic decision problem domain. In this domain, we also see that there definitely exist applications where a standard approach and tool can make sense: for instance, the “strategic distribution network optimization” problem. It is important to note in this context that, even though the chosen tool “CAST” initially had some shortcomings in modeling certain special characteristics of the BASF business, the provider was flexible in adjusting and extending the OR model according to these needs in a very short time. Thus, it could be achieved that the “standard” covers most of the relevant decision problem aspects and is appropriate. This state could only be reached, however, through the exchange of OR experts on the side of BASF and the solution provider.

In the area of APS some of the existing providers offer limited flexibility and only insufficient or complicated interfaces to mitigate potential shortcomings in their systems. One important decision problem domain that they address is the tactical one, *e.g.*, mid-term production planning. Are those systems appropriate for this task despite their inflexibilities?

In general, if a system does not offer easily usable interfaces and thus is inflexible, the buyer and user of such a system has to make sure that (i) the available model in this system covers all relevant aspects encountered in practice and (ii) the available solution algorithms are always up-to-date. With respect to (i) we know from our own experience that the formulation of a generally applicable model is nearly impossible. Kallrath and Maindl (2006) (Chapter 8) formulate a rather general model which contains most features of production planning and distribution planning one encounters in the process industry. However, there are still certain aspects that this model does not cover as recent projects conducted by the first author show. Therefore, the application of such a standard APS model in a company requires a good understanding of those aspects that are considered in the tool, on the one hand, and those aspects that are truly relevant from a business point of view, on the other hand. Only if there is a match between those two sides, is the system solution appropriate.

With respect to (ii), the algorithmic part of the solution, the developments move at a high pace. Some of those developments are driven by commercial providers, *e.g.* when it comes to solvers such as CPLEX, Gurobi or Xpress. Others are driven more heavily by the scientific community. The latter makes it challenging for a commercial solution provider to keep up when it comes to integrating the latest developments into its solution. By neglecting those developments a company might forgo considerable saving potentials, however. A good example is “R”, a free software environment for statistical computing and graphics (*cf.* <http://www.r-project.org/>; accessed on 6/3/2014). Due to its special open source setup the entire “R” community acts as developers and provides the latest developments to the others. Commercial software providers in this area struggle heavily in offering similar functionalities.

In both respects, one can try to push the provider to upgrade its standard. This might take some time, however. Alternatively, one can ensure that the “standard” tool offers flexible interfaces that allow for the extension by tailor-made solutions through the exploitation of the available in-house OR expertise. By making use of the latest technologies, those solutions provide benefits to the businesses that the standard

cannot deliver – at least not in the short term. Trimming a real-world decision problem such that it fits the “standard” is most likely a high price to pay in terms of the resulting solution quality. In the end, there is the risk of losing the overall trust in such IT solutions.

The challenging and critical task certainly refers to the assessment of the appropriateness of the standard models and tools for the concrete business setting. The misfit might be evident and therefore easily detectable by anybody or it might be rather subtle and thus require special OR knowledge. Criteria of interest when making a decision about a standard vs. a tailor-made solution are, amongst others:

1. What is the purpose of the model?
2. How well suited is the standard (APS) model? Does it fit the reality or is it *necessary to change the reality* and what are the consequences for the solution quality? Can the standard model be extended, if necessary?
3. What are the costs?
4. What is the value of having a transparent tailor-made in-house model versus a black box model, for instance, a standard APS?
5. What should be the life-time of the model and do we expect modified requests towards the model over the years? (The up-front investment might be significant but can easily pay off over the years if more requests have to be served.)

The overall task actually calls for a joint effort and close collaboration between three parties as equal partners:

1. SCM experts for process knowledge and coordination
2. OR experts for bringing together the business requirements with the appropriate methods
3. IT experts for providing the required data, interfaces, and implementation.

The collection of the business requirements should be jointly done by SCM and OR experts, because in this phase one needs to distinguish relevant from irrelevant aspects already – from a supply chain point of view, but also from an OR solution perspective.

SCM and IT experts are usually available within every company. OR experts, on the other hand, are not that common in companies. (Anglo-American companies might be the exception here.) So, the natural question arises: Does it pay off to have an in-house OR unit?

5.2.3 The value of in-house OR experts

Since decision-making is expected to become more and more data-driven in the future (see Waller and Fawcett (2013)), in-house OR experts or data scientists as they are also sometimes called can bring considerable value to the table. On the one hand, the above-mentioned examples clearly show that, with a relatively small investment (in OR resources and IT), oftentimes large saving potentials can be identified and eventually realized. On the other hand, internal OR knowledge is also valuable in the decision-making process concerning outside (out-of-the-box) solutions. In particular, in the current wave associated with

the buzzword “Big Data” a lot of (consulting) companies market their solutions by promising enormous improvements.

In-house experts take an unbiased view of the methods and technologies, act in the interest of the company, and thus can help to really separate the wheat from the chaff. Oftentimes external companies focus on one specific method that might work well in one particular business context, but not in another. By having a broad methodological toolset at hand, thorough application expertise as well as further company-internal knowledge, in-house OR experts can help determine the appropriateness of commercial solution. They can provide valuable support in conducting necessary tests (“proof of concepts”) to arrive at a reliable result and assess the true value of such a solution for the entire company.

Since no model/tool can ever cover all possible real-world aspects, part of this value also refers to the tool’s flexibility. A flexible commercial solution can be used as the basis and thus “standard”, to which tailor-made variants are attached by the in-house OR experts, if the need arises. The flexibility and openness of the tool needs to be assessed in the selection process. Through such a setup one can combine the strengths of a commercial “standard” solution in one area with dedicated solutions for specific business requirements developed by the in-house team. Thus, prompt responses to new business requests can be delivered as well. Moreover, the latest scientific developments with respect to models and algorithms can be exploited to generate value for the company. There is no need for waiting until the commercial tool provider enhances the solution in this direction.

6 Conclusions

In this article we have highlighted the application of operations research (OR) at BASF in the area of supply chain management (SCM) through the use of selected strategic, tactical or operational examples. Besides annual cost savings ranging between several hundred thousand and several million €, the project partners appreciate the transparency and quantitative decision basis obtained through the developed models as a great value of the mathematical optimization approach.

From our experience, the special characteristics encountered in the process industry often call for a modification or enhancement of “standard” OR models and might hamper the direct use of readily available commercial software solutions. This refers to basically all decision-making time horizons from strategic to tactical to operational with few exceptions. For this reason it seems worthwhile to ensure that “standard” solutions and tools offer enough flexibility to extend them by tailor-made models and methods, if required, in order to generate appropriate and meaningful results for the businesses to support their planning tasks. The decision about when to deviate from the standard is a complex one, because it involves various aspects and requires knowledge from different parties: SCM, IT, and OR experts. Therefore, this should be a joint undertaking.

Even though OR is a facilitator for better decision-making, OR by itself is certainly not sufficient for the success of a project or solution. From the projects at BASF we know that it takes specialists from all relevant fields (mathematics, engineering, logistics, procurement, controlling, supply chain management, etc.) to form an intercultural and interdisciplinary team in order to maximize the project return. Communication across

the borders of each project member's field of expertise is a challenging task. In the end the richness of the ideas, views and methodologies is key to a project's success. At BASF, we call this the *best team* strategy.

Acknowledgement

The authors are grateful for valuable input and suggestions from Anna Schreieck and Jens Schulz from *Scientific Computing*, which substantially improved this paper. Furthermore, we would like to thank all the project partners for their collaboration and input that contributed significantly to the projects' success.

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